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RESEARCH ARTICLE

TRAVEL RECOMMENDATION SYSTEM WITH MULTI-POINT-OF-INTEREST BASED ON COLLABORATIVE FILTERING

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ABSTRACT

Location-based social networks provide an interface for users to share their locations and write reviews about interesting places of attraction. The shared locations form the digital footprints, in which each user has many connections to many locations. It indicates user preference to locations. In this paper, an approach has been proposed for travel recommendation to help users make travel plans. The approach utilizes data collected from location based social networks to model a set of suggestions. It determines users' preferred destinations using collaborative filtering approaches. Recommendations are generated by jointly considering user preference and location co-relation, on this basis a travel route planning algorithm has been designed to generate travel packages. In this paper a prototype system has been developed, which obtains users' travel demands from mobile user and generates travel packages containing multiple points of interest and their visiting sequence.

INTRODUCTION

Any form of social experience via the interactions between different people can be defined as social networking. Online social networking has been very popular over the last few years due to the ease of using it and the benefits people are getting from it. However, the concept of social networking is not new. People have been using different forms of social network for many years and have benefitted from it. Table.1.1 shows the increasing number of users on social networking sites (www.statista.com). People get involved in social networking for many reasons, these could be for the need to keep in touch with friends and family, for the curiosity to know about how others are doing, the urge to know about more information, for information giving and so on. Due to the availability of various internet devices such as desktops, laptops, mobile phones and tablets, participating in social networking has become easier in recent years. As a result, social networks have gained tremendous popularity. Location based social networks are also attracting users. With the increasing popularity of smart-phones, location-based social networks have millions of users. The users not only explore location-aware information, but also write reviews and share their experiences. User mobility and trajectory provide the information about their interest and information about the visiting place.

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They share their views about the events to the other user on the social network and the user who are having same interest come to know about these new places. Location popularity depicts the ability of a location to attract the users to visit it. The higher the popularity of a location, the more users share check-in status with various other users. Based on users' interest, various recommendation system name evolved. These systems are a subclass of information filtering system that seek to predict the "rating" and "preferences" that a user would give to an item. Recommendation Systems have become increasingly popular. Recommendation systems are utilized in variety of areas including user recommendation for movies, music, travel, books, financial services, twitter pages and many more. One of the recommendation systems could be travel recommendation system. While planning a vacation, people generally ask their friends or family for suggestions. This trivial way is inconcise and is focused on friend's individual choices. To solve this problem, a travel recommendation system could be very beneficial. To form travel recommendation system, social networks are used to collect the information. This has turned out to be an effective way of collecting information from which users' interest can be filter out. In this paper, a recommendation travel package with multiple point of interest has been proposed that is based on user visited locations collected from twitter, which is one of the most popular location based social network. Millions of users use twitter to tweet their views and "check in" for sharing locations, events, and feelings with their friends.

Table 1. Statics of social network users

Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
No. of users in billion	0.97	1.22	1.40	1.59	1.91	2.14	2.34	2.51	2.67	2.82

The rest of the paper is organized as follow: Section 2 discuss related work related to travel recommendation system. Section 3 deals with proposed approach to form recommendation system. Section 4 shows results regarding proposed approach. Section 5provides conclusion remarks.

Related Work

Travel recommendation system can be classified on the basis of approach used to form recommendation system (Chia-Chuan Yeh, 2010). Tang, J et al. explained that content-based recommendation methods will look at the user profile and item features to find good recommendations. The system recommends those items that exhibit similar characteristics to the user's preferences in the past (Lakshmanan, 2011) Romeo et.al. explained a framework which uses the prior knowledge and generates result what the users expect from a recommendation task. Recommendation system used Page Rank-style method with respect to target user's preferences for personalization. Because of the emerging trend in research on recommender systems to design a system which could recommend multiple results instead of single result. When the recommender systems have only small amount of data or do not have base information for generating suggestions, collaborative models resolve that problem. Such problem is called cold start problem. The usage of similarity and differences between users' interests is mostly used by many recommendation models. Finally, by comparing the users or items, different similarity measures were described (Anishya, 2015). Hsieh.et.al. explained that the collaborative filtering is the primary approach of any recommendation system. It provides a recommendation which is easy to understand. It is based on similarities of user opinions like rating or likes and dislikes. So the 'recommendation provided by collaborative cannot be considered as quality recommendation. Recommendation after association rule mining is having high support and confidence level. So that will be considered as strong recommendation (Romeo, 2013). Lakshmanan et. al. proposed a recommendation system based on the central idea. The usual recommender systems provide users with a list of recommendations without any assessment about target user's interest. Hence this system recommends top-k results for users to choose from. The recommended result consists of items in the form of sets or sequences based on user preferences like budget, location etc. The system uses rating information from underlying recommender systems, allows flexible package configuration and incorporates users cost budgets on both time and money. It had good graphical user interface which could let users to customize the returned composite recommendations and took into account external local information (Zhiwen Yu, 2014). Jiang, et.al. proposed User-based Collaborative Filtering for Tourist Attraction Recommendations. It describes the way of recommendation by using number of visits and takes it as feedback to generate the results. Personalized recommendations help users in getting the list of items that are of user preference. Majority of systems use Collaborative Filtering techniques to generate recommendations to their users. This system implements a filtering technique called as hybrid approach for generating personalized recommendations for user. Hybrid Approach is the combination of content-based filtering and collaborative filtering. Collaborative Filtering encounters the problems of Scalability when the number of users increases and sparsity problem (Yuan, 2010), for new users (Xinhuan Chen, 2015), Romeo et.al. Describes the hybrid filtering which combine the both approaches content and collaboration. In this recommendations are generated through profile matching (Yu, 2011). Girijamma proposed a hybrid approach with use of tags, geo-tags image is proposed in this paper. User based collaborative filtering is used to create suggestions for the users (Zhang, 2011). Lou et.al. explained that recommendations are generated by jointly considering user preference and spatiotemporal constraints. To generate travel packages a heuristic search-based travel route planning algorithm was designed. A prototype system was developed which obtained users travel demands from mobile client and thus generated travel package containing multiple points of interest. This approach is improvement in accuracy and diversity according to the experimental results. To form recommendation system prediction is the main factor. Different researchers have used different approaches for prediction of recommendation.

Jyoti et.al. presented a novel approach for finding the user sessions from the web log and then applying rough set clustering to cluster the important sessions based on the maximum pages visited. User sessions are grouped to improve prediction accuracy as data mining techniques are applied on session clusters and not on all sessions and hence the complexity is reduced Jyoti et al. (2009) proposed a novel approach for predicting user behavior for improving web performance. In this prediction and prefetching is done both by collaborating information from user access log and website structure repository. This work overcomes the limitation of path completion. Application of Petri Nets for extracting web site structure helps in path completion process, better prediction, decreasing web latency and improving web performance.

Table 2.1 shows the comparison between different approaches used by researchers to form the recommendation system[12]. Recommender system is used extensively these days that it has become a preferable choice. All the different approaches explained above are given by many researchers has been use different factors to make the recommendation system more effective. The next section describes the proposed approach in detail.

Proposed Approach

Due to exponential growth of internet, everyone is dependent on internet to get even a small piece of information or suggestion. It has become a big concern to provide the better suggestions to users. As more and more services turning online, recommendation is also a form of online suggestion where a better result of recommendation can be fetch in minimum time. To provide better suggestions in less time, travel based recommendation system plays an important role. Various approaches has been used for predicting better recommendations for the users. In these approaches collaborative filtering is mostly use by the researchers. Collaborative filtering remove the limitation of cold start i.e. for a new user what should be the recommendations.

Table 2.1 Comparison of various approaches

S.N	Approach	Content Based	Collaborative	Hybrid	Social Network
1.	Correa [2]		✓		
2.	Lakshmana[4][18]		✓		
3.	Jiang[5]		✓		
4.	Romeo [6]	✓			✓
5.	Lou [8]	✓	✓		
6.	Girijamma [9]			✓	
7.	Chen[10]				✓
8.	Ying Zhang[11]				✓
9.	Xing[12	✓			✓
10.	Feng[13]				✓
11	HanSu[17]		✓		✓

However, there are inherent problems to collaborative filtering approach. It gives the suggestion with a large number of results, so the problem of cold start can be overcome but it cause high level of scarcity in database (Yuan, 2010). All the results present in database related to that user are provided as suggestion or recommendation. It does not provide better understanding that which suggestion should be taken out. Plus, second problem is that it provides the single-point of interest. So there is need to filter the result in the form that it can give proper sequence of recommendation with multi-point of interest. Fig. 3.1 shows the framework of proposed approach in which data that has been collected from social network. Three modules (Repository formation, Prediction Engine and Recommendation Engine) have been used to filter out information and then form the recommendation system.

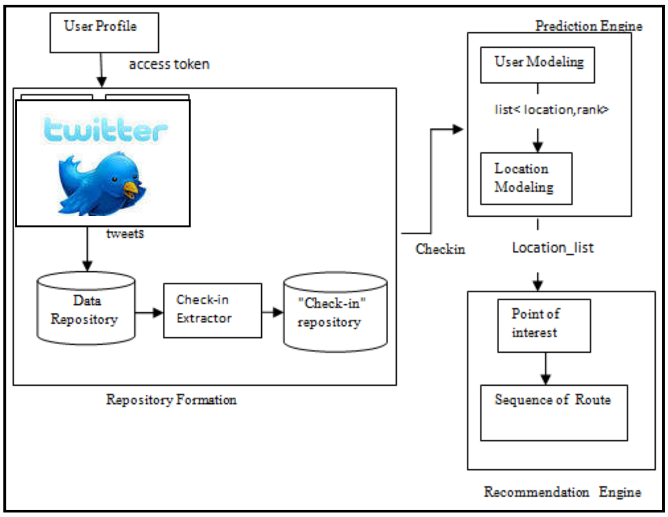

Fig. 3.1 Framework of Travel Recommendation System

Data Repository Formation

To fetch the real time data from twitter timeline some steps are to be followed:

Twitter Application: *Firstly, there is need to form a twitter application from developer's option that is connected to twitter account. After creating developer application there is need to get the access token for type of application (Read, Read and Write, Access Direct Messages) has been created. It provide OAuth setting to get the consumer key. Consumer key is unique key for every application and provide the authorized access to fetch the real time data of users' timeline. Twitter4j API: twitter4j is a java application based API. After creating twitter application, to extract the real time data from user timeline there is need to use twitter4j API. It help to extract recent tweets of user for which access token has been issued. Twitter4j also help to verify the authenticity of the access token. Based on the OAuth specifications, it extract the tweets. Twitter4j API: After fetching the tweets there is need to store the tweets by which tweets can be identified according to particular user, time and type of tweets.*

When data repository is formed next step is to predict the ranking of locations collected from twitter timeline.

Prediction Engine

Prediction engine is used to predict the target location based on the "check-in" received from data repository. It further ranks the list of locations predicted by the prediction engine. Firstly user modeling provide the visiting frequency of locations and then location dependence calculates the location co-relation in the list of locations. It does this job in two steps:

User Modeling: *User modeling extracts the data from user timeline. Usually user share their information in the form of reviews or check-in. Review of any place gives the information about the likes and dislikes of the user. Check-in is also an important part to extract the information. It gives the actual information about the visiting places, where traditional browser fails. From a user timeline, "check-in" tweets of followers and followees are extracted with the help of twitter4j. These tweets are filtered by collaborative approach to get the locations.*

To obtain prediction based on user modeling for each location category frequency of the visits is calculated. F_{ck} is the user's preference of the C_{kth} location category of type i, and (u, o) is the number of times that user u has visited location o.

$$F_{ck} = \sum_{0}^{i} VC(u, o)$$

To obtain the visited frequency set, a list is formed that shows the location and rank according to number of "check-in" tweets.   is representation of list according to :

$F = <F_{c1}, F_{c2},..., F_{ci}>$.

Location Modeling: Location modeling is the component in which various location dependence has been calculated. To provide the better recommendations to users based on the locations, there is need to model various locations which are nearby to each other. A sequence of filtered location can provide better understanding to user that from where to start with and what should be the better sequence to visit a city. It calculates the co-relation exist between two visiting places. For example, travelers tend to visit the India Gate, Indira Gandhi National Centre of Arts, and Vigyan Bhavan in Delhi together, as these three attractions are close to each other. Therefore, the travel package recommendation system recommends a set of related locations rather than unrelated ones. It is useful to explore the frequent sequences and to use them to reduce the computational complexity of the recommendation engine. The location list according to the visiting order of locations in user check-in records will be more feasible to user. The arccos function [19] is use to extract the frequent location sequences.

$$\text{Dis}(L1,L2) = R.\arccos(c).\frac{\pi}{180}$$

Here L1 and L2 are the two locations. Dis is the distance that is to be calculated. arccos(c) calculates the change in the longitudinal and latitudinal values from a location to next one. Preference of the location is given to which get the least value in the Dis () function. Arccos function gives the result in the form of longitude and latitude values. It identifies the preferences of the location within the radius that has been used to find the co-relation between the various visiting places. Preferences of the co-relation existence has been given according the least value of the function. It takes various locations and find the co-relation between these locations. Map API has been used to calculate it which help to find the longitude and latitude of the next location that should be visited.

Recommendation engine

To form the recommendation engine Google map API has been used. With the help of Google map markers for point of interest are calculated and then sequence of these point-of-interest has been shown to recommend the visiting sequence. Data that has been filtered to form the preferences of the visiting sequences. Now there is need to form these locations on the Google map. It will provide the result of recommendation in more attractive form. Fig3.2 shows algorithm for recommendation system.

To form the recommendations it calls functions that are User_Modeling and Location_Dependence. Fig.3.3 explained user modeling algorithm that take the collected tweets as input and according to the users' number of visit of particular location, it provides the ranking to that location. It gives the ranked locations as output.

After user modeling, it goes to location dependence as explained in Fig.3.4. Location Dependence takes the list of locations and then finds co-relation between locations to form the sequence of location for a particular city. After computing location dependence, a list of co-related location is filtered that shows the multiple point of interest. Now, these points of interest are used by recommendation engine to provide the suggestion to users as shown in fig.2 to form the recommendations. Impirical Results. The recommendation system is implemented using JAVA 1.8 on intel core i5 processors and4-GBmemory.

```
Recommendation()
{
//input: user enters name of city to be visit.
//output: sequence of markers on map.
String s="enter city";
call User_Modeling();
call Location_Dependence();
compute markers as point of interest on map
Display sequences of locations.
//GOTO Recommendation()
}
```

Fig. 3.2. Algorithm for recommendation system

```
User_Modeling ()
//inputs: crawled tweets from user timeline
//output: preferences according to user profile
String CITY="keyword for check-in";
list<s,rank>="collected tweets" //store the tweets
String tweet[]= StringTokenizer.list //tokenization of tweets
for(i=0; i<=length.CITY)
{
Compare(Tweets,CITY)// compare tokenized tweets with entered string
{
if(Tweets[]==0)
{
"error in crawling tweets"
}
if(wordMap.containsKey(rank)) //compute the frequency of every location
{
wordMap.put(rank, wordMap.get(rank)+1); //increment if reappe
}
else
{
wordMap.put(tmp, 1);
}
for(Map.Entry<String, Integer> entry:list) //form the list
{
Print(entry.getKey(),entry.getValue());
}
//GOTO Prediction_on_user()
}
```

Fig. 3.3. Algorithm for user modeling

At the client end, an application based on Android platform was developed as the user interface. Users' travel demands, including name of place to visit, is entered through the user interface Fig.4(a). Example recommendation results that consist of travel packages are in Fig. 4(a). Users can browse package, such as the location of destinations and the suggested travel order of destinations in the map. Fig. 4(b) shows the layout of map which ask to enter a city that the user want to visit. Fig. 4(b) shows the output that comes after entering the city. It shows a sequence of various locations of the city that user entered.

Results are compared with two algorithms. The first one is the Random recommendation, where the point of interest are randomly recommended to users. The other is the Hottest-first algorithm, where the top-k hottest point of interest are selected. These algorithm shows the 25% of the results[18] to give the recommendation.

```
Location_Dependence()
{
//input: list of location preferences
//output: Re-ranked list of locations
integer i ="radius ";
list<s,long,lat,d,rank>.location();
for(i=0 to length of list ;i+10)
{
for(list[j]=0 to length of list)
{
list<s,long,lat,dis,rank>.arccos(i);
{
if(list.dis is minimum)
{
wordMap.put(rank,wordMap.get(rank)+1); //increment in rank
}
}
for(Map.Entry<String, Integer> entry:list) //form the list
{
Print(entry.getKey(),entry.getValue());
}
//GOTO Location_Dependence()
}
}
```

Fig. 4. Algorithm for location dependence

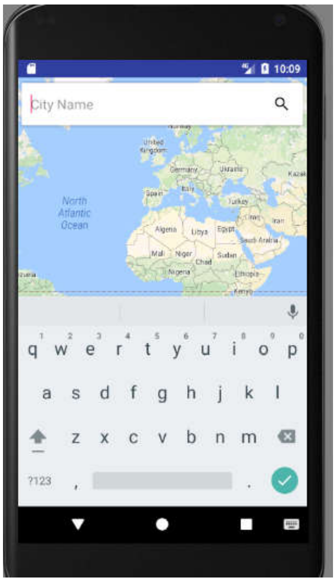

Fig.4(a)

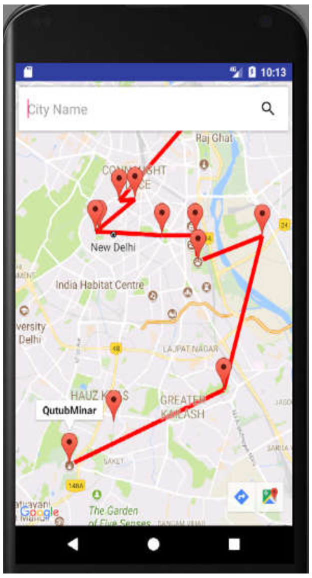

Fig.4(b)

Implemented algorithm provides better results in terms of collaborative filtering in which recommendations are in form of sequences of ranked locations. It gives complete package of various locations instead of independent locations.

Conclusion

We find the problem of travel package recommendation based on user check-in. The system not only helps users find interesting locations, but also generates travel packages consisting of different types of locations and visiting sequences. The location popularity and user preference for point of interest are modeled by utilizing features of social networking sites that is user check-in records. Based on these models, we then determine the locations based on multi point of interest. We implement a prototype recommendation system for a mobile client in which user can get suggestions for any city and from anywhere.

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